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# Electric Storage in California's Commercial Buildings

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## Abstract

Most recent improvements in battery and electric vehicle (EV) technologies, combined with some favorable off-peak charging rates and an enormous PV potential, make California a prime market for electric vehicle as well as stationary storage adoption. However, EVs or plug-in hybrids, which can be seen as a mobile energy storage, connected to different buildings throughout the day, constitute distributed energy resources (DER) markets and can compete with stationary storage, onsite energy production (e.g. fuel cells, PV) at different building sites. Sometimes mobile storage is seen linked to renewable energy generation (e.g. PV) or as resource for the wider macro-grid by providing ancillary services for grid-stabilization. In contrast, this work takes a fundamentally different approach and considers buildings as the main hub for EVs / plug-in hybrids and considers them as additional resources for a building energy management system (EMS) to enable demand response or any other building strategy (e.g. carbon dioxide reduction). To examine the effect of, especially, electric storage technologies on building energy costs and carbon dioxide (CO<sub>2</sub>) emissions, a distributed-energy resources adoption problem is formulated as a mixed-integer linear program with minimization of annual building energy costs or CO<sub>2</sub> emissions. The mixed-integer linear program is applied to a set of 139 different commercial building types in California, and the aggregated economic and environmental benefits are reported. To show the robustness of the results, different scenarios for battery performance parameters are analyzed. The results show that the number of EVs connected to the California commercial buildings depend mostly on the optimization strategy (cost versus CO<sub>2</sub>) of the building EMS and not on the battery performance parameters. The complexity of the DER interactions at buildings also show that a reduction in stationary battery costs increases the local PV adoption, but can also increase the fossil based onsite electricity generation, making an holistic optimization approach necessary for this kind of analyses.

## Keywords

California, CO<sub>2</sub> emissions, distributed energy resource optimization, electric storage, electric vehicles, energy costs, microgrid

## 1 Introduction

In the past years considerable progress in battery technology has been made. This led to significant improvements in the technical characteristics and costs of batteries [1]. This improvement has amplified their field of application. High performance batteries found their way into the automotive

field, where they are forming the core of advanced propulsion technologies such as hybrid, plug-in hybrid or pure electric power train systems. They also increased their relevance as stationary energy storage devices for power systems applications. Stationary batteries, whose application field used to be limited to islanded networks and buildings without grid connection, can now become more relevant for energy management in buildings and microgrids with e.g. installed Photovoltaic (PV) [2].

This paper analyses the effect of this progress on local power system applications including both stationary and mobile battery storage, using the Distributed Energy Resources Customer Adoption Model (DER-CAM) [3], [4], [5], [6]. DER-CAM is a mixed integer linear program (MILP) that defines optimal adoption and use of distributed energy resources (DER) in a microgrid or building complex in order to minimize costs or CO<sub>2</sub> emissions. A microgrid is a group of interconnected loads and DERs within clearly defined electrical boundaries that acts as a single controllable entity with respect to the grid. More detailed information on microgrids can be found in [7]. Berkeley Lab has been developing the DER Customer Adoption Model (DER-CAM) for more than 10 years and its basic mathematical formulations are documented for example in [6] and [15]. Its optimization techniques find both the combination of equipment and its operation over a typical year to minimize the site's total energy bill or CO<sub>2</sub> emissions, typically for electricity plus natural gas purchases and for amortized equipment purchases. This model outputs the optimal distributed generation (DG) and storage adoption combination and an hourly operating schedule, in addition to the resulting costs, fuel consumption, and CO<sub>2</sub> emissions. This work uses the latest DER-CAM version, which enables EVs and looks into the interaction of electric storage with other DERs as e.g. photovoltaic (PV) or combined heat and power (CHP) in commercial buildings and microgrids, assuming different technical characteristics for future years. Thus, the main objective of this paper is to determine the economic and environmental impact of building connected electric cars and stationary storage in California. For this purpose, the California End-Use Survey (CEUS), which holds approximately 2,700 building load profiles for the commercial sector in California [16] was used as basic input data. These hourly load profiles are needed to make optimal decisions on the operation of the DG equipment and EVs, which influence the optimal DG investment capacities because DER-CAM considers amortized investment and operation costs. A subset of 139 representative building load profiles for buildings with electric peak loads ranging between 100 kW and 5 MW are used as input for DER-CAM. These 139 buildings account for approximately 35% of total statewide commercial sector electric sales [4]. These load profiles, combined with technology costs and performance data, will serve as input for DER-CAM, and DER-CAM will then determine the optimal adoption of DER and usage of stationary and mobile storage on a building level in 2020. DER-CAM will act as simulated building energy management system (EMS), which can use the EVs connected to the buildings for load shifting. To take into account potential improvements of battery technologies, the robustness of the results with respect to changes in storage specific parameters, such as charging and discharging rates and efficiencies are analyzed in detail, and the interaction with other DERs is shown.

Several papers analyze the effect of renewable energy sources and EVs on the power grid and electricity prices. The possibility of providing macro-grid ancillary services and storage capabilities by usage of plug-in hybrid electric vehicles (PHEVs) is analyzed in [8]. [9] and [10] analyze the impact of EVs on the macro-grid load and electricity prices. [11] looks into different battery technologies suitable for renewable technologies as PV and also how these technologies can be assessed on a technical level by Simulink [12] or Homer [13]. In contrast, this work and DER-CAM uses a building-centric economic and environmental approach since buildings establish the link between EVs and the wider macro-grid and looks into the cost and CO<sub>2</sub> benefits for buildings adopting DERs in California. This building-centric approach implies that every single building is optimized individually based on

the building owners expectations and views. Furthermore, many DERs in a building will be influenced by EV batteries. Also, stationary storage in buildings attracts more research attention, which can create competition between mobile storage and stationary storage. On the other hand, when mobile storage is not suitable for EV usage anymore, it can be recycled and used as stationary storage in buildings, where the battery specifications can be relaxed. This post-vehicle “battery-to-grid” application of EV batteries attracts the attention of researchers and the California Energy Commission (CEC), which may also create opportunities for EV batteries [14]. The DER-CAM building-centric approach allows us to use it as EMS emulator and the building can use the mobile storage and stationary storage for tariff-driven demand response. By using EVs connected to the buildings for energy management, the buildings could arbitrage their costs. However, with this approach we do not optimize storage technologies in isolation and treat all possible building DERs as equal options. In this way it is possible to model interactions and competition between DER technologies and interesting effects can be seen. For example, [17] shows that PV and stationary storage can be in competition depending on the optimization strategy (costs versus CO<sub>2</sub>). Voltage and Var support is not considered in this work, but currently under design in DER-CAM. Also, this work assumes a deterministic view of the future and does not consider uncertainty in e.g. driving patterns. Thus, the results presented in this work should be interpreted as an average or benchmark case given planned behavior or driving patterns. A full stochastic based version of DER-CAM is currently under development.

The paper is structured as follows:

- Section 2 shows the basic methodology of DER-CAM and focuses particularly on aspects related to the adoption and use of electric storage capacities.
- Section 3 presents the input data used for the analysis, focusing especially on techno-economic specifications of electric storage technologies.
- Section 4 illustrates and discusses the results of the analysis.
- Section 5 draws conclusions.

## 2 Methodology

### 2.1 DER-CAM

DER-CAM is a mixed-integer linear program (MILP) written and executed in the General Algebraic Modeling System (GAMS). Its objective is typically to minimize the annual costs or CO<sub>2</sub> emissions for providing energy services to the modeled site, including utility electricity and natural gas purchases, plus amortized capital and maintenance costs for any DG investments. The approach is fully technology-neutral and can include energy purchases, on-site conversion, both electrical and thermal on-site renewable harvesting, and partly end-use efficiency investments. Its optimization techniques find both the combination of equipment and its operation over a typical year that minimizes the site’s total energy bill or CO<sub>2</sub> emissions, typically for electricity plus natural gas purchases, as well as amortized equipment purchases. It outputs the optimal DG and storage *adoption* combination *and* an hourly *operating schedule*, as well as the resulting costs, fuel consumption, and CO<sub>2</sub> emissions. Furthermore, this approach considers the simultaneity of results. For example, building cooling technologies are chosen such that results reflect the benefit of electricity demand displacement by heat-activated cooling, which lowers building peak loads and, therefore, the on-site generation requirement, and also has a disproportionate benefit on bills because of demand charges and time-of-use (TOU) energy charges. Site-specific inputs to the model are end-use energy loads, detailed electricity and natural gas tariffs, and DG investment options. For a more detailed description of the DER-CAM model see [3], [4], [5], [6].

Figure 1 shows a high-level schematic of the building energy flows modeled in DER-CAM. For this we use Sankey diagrams, which show in a graphical way how loads can be met by different resources at given efficiencies. Thus, a Sankey diagram provides a full view of possible resources that can be considered within the optimization. Available energy inputs to the site are solar radiation, utility electricity, utility natural gas, biofuels, and geothermal heat. For a given site, DER-CAM selects the economically and/or environmental optimal combination of utility electricity purchase, on-site generation, storage and cooling equipment required to meet the site's end-use loads at each time step. In other words, DER-CAM looks into the optimal combination and operation of technologies to supply the services specified on the right hand side of Figure 1. All the different arrows in Figure 1 represent energy flows and DER-CAM optimizes these energy flows to minimize costs or CO<sub>2</sub> emissions. Black arrows represent natural gas or any bio-fuel, light grey represents electricity, and grey heat and waste heat, which can be stored and/or used to supply the heat loads or cooling loads via absorption cooling.

## 2.2 The specific case of electric storage in DER-CAM

The basic assumption within this paper is that EV owners drive to different work places and connect their cars there. Once EVs are connected to commercial buildings, electricity from their batteries can be transferred to and from the sites. These commercial buildings create commercial microgrids as shown in Figure 2. The EMS or microgrid controller can use this additional battery capacity to lower its energy bill and/or carbon footprint. Whenever possible, economically attractive energy from a renewable energy source or CHP system at the commercial building could be used to offset EV charging at home at the residential building (see also Figure 2). The total mobile storage that can be used by the building is constrained by the available parking space and the derived maximum number of electric vehicles with a defined nominal storage capacity of 24 kWh per electric vehicle. For technical reasons the state of charge of the EV storage has to remain within the range of 20% and 90% state of charge (SOC), which means that the useable capacity is only 70% of the nominal capacity.

Different connection periods apply for different commercial buildings, depending on the business type. For all building types, except restaurants and hotels, used in this work the cars connect around 8:00 – 9:00 in the morning to the commercial building and disconnect around 18:00. For restaurants and hotels different connection periods are assumed. Restaurants assume EV connection periods between 18:00 and 21:00. For hotels it is assumed that cars are connected to the commercial microgrid between 19:00 and 8:00. In reality, these connection periods are of stochastic nature, and therefore, different connection periods have been modeled for different building types. In this analysis every car is allocated to the same commercial microgrid, which is based on the defined schedules and no switching/driving between commercial building is assumed. Finally, to ensure certain driving patterns, EV state of the charge (SOC) constraints are enforced when connecting ( $SOC_{i,in}$ ) and disconnecting ( $SOC_{i,out}$ ) to the commercial microgrid. EVs connect with an average SOC of 73% to the commercial building and leave with no less than 32% to ensure the trip home. Between the 73% and 32% SOC the building EMS can manage the EV batteries to achieve the objective of minimizing costs or CO<sub>2</sub> emissions. The mobility patterns and driving schedules represented in this case study are based on information about commuters from the National Household Travel Survey (NHTS) in 2001. It is the inventory of daily and general, short to long distance travel information. i.e. demographic characteristics of households, people and vehicles from a sample size of 69,817 households (see [18]). The derived average daily commuter travelling distance for passenger cars is 24 miles (38km). This corresponds roughly with 4 kWh [19] of energy consumption for one trip of 12 miles (19km).

In this paper, DER-CAM is used to find the optimal charging and discharging schedule for the EV and stationary batteries in a microgrid or commercial building with other DERs. In other words, DER-CAM is run for every microgrid (see Figure 2) considering the different EV and home charging



constraints. Decision variables are, therefore, the operational levels of all available energy sources so that energy loads are met at the microgrid as well as the optimal installation or EV connection capacity. Included in these variables are utility energy purchases, local energy production, and storage interactions, which are the focus of this paper. In the case of EVs it is assumed that the EV owner will receive compensation for battery degradation caused by the commercial building EMS and is reimbursed for the amount of electricity charged at home and later fed into the commercial microgrid (see equations 1 & 5). On the other hand, if the EV is charged by electricity originating from the commercial building, then the car owner needs to pay the commercial building for the electricity.

$$C_{EV\ bat} = E_{EV} * CL * RC_{bat} \quad (1)$$

$C_{EV\ bat}$	EV battery degradation annual costs caused by the commercial building or microgrid, \$
$E_{EV}$	total annual electricity exchange through the EV battery, caused by the commercial building or microgrid, kWh
$CL$	capacity loss factor, dimensionless
$RC_{bat}$	replacement cost of the EV battery, \$/kWh

The monetary losses attributable to charging and discharging as well as the decay will be covered by the commercial building. However, since this work also reports on the environmental impact of EVs connected to commercial buildings, the modeling of the marginal CO<sub>2</sub> emissions is important. The marginal CO<sub>2</sub> emissions when the EVs are plugged in at residential buildings for charging are tracked as this is necessary to be able to calculate the proper CO<sub>2</sub> changes in the commercial buildings (see equations 7 & 8). This becomes even more complex if the EVs are connected to different buildings during a certain period of time. However, multiple building connections are not considered in this work.

The high-level formulation used in DER-CAM follows the standard linear programming approach:

$$\begin{aligned} \text{Min } f &= c^T x \\ \text{s. t.} \\ Ax &\leq b \\ L &\leq x \leq U \end{aligned} \quad (2)$$

where:

$c$	cost coefficient vector
$x$	decision variable vector
$A$	constraint coefficient matrix
$b$	constraint coefficient vector
$L$	decision variable lower boundary vector
$U$	decision variable upper boundary vector

This translates to DER-CAM in the simplified mathematical formulation explained below, where an emphasis is given to electric storage specific formulation. The full detailed mathematical formulation of DER-CAM is roughly 17 A4 pages.

#### *Input Parameters*

##### *a. Indices*

$m$	month index (1,2,... 12)
$h$	hour index (1,2,... 24)

##### *b. Market data*

$C_{fix\ m}$	fixed monthly electricity costs, \$
$C_{STfix}$	fixed stationary storage costs (costs for engineering, permits, etc. which do not depend on the size of the project, \$
$C_{STvar}$	variable stationary storage costs, \$/kWh
$l_{ST}$	stationary storage lifetime (based on the number of charging and discharging cycles), years
$r$	interest rate, dimensionless
$CO_{2\ EV-home\ m,h}$	macrogrid $CO_2$ emission during home charging period, $kgCO_2/kWh$ . These are the $CO_2$ emissions of energy transferred to the commercial building/microgrid. $CO_{2EV-home\ m,h}$ is calculated based on the emissions when the EV is connected to the residential building.

c. *EV parameters*

$c_{EV}$	EV battery capacity, kWh
$\overline{cr}_{EV}$	EV battery maximum charge rate, dimensionless
$\overline{dr}_{EV}$	EV battery maximum discharge rate, dimensionless
$p_{EV}$	EV electricity exchange price, \$/kWh. Set to residential charging rate for EVs
$\overline{SOC}_{EV}$	EV battery maximum state of charge, dimensionless
$\underline{SOC}_{EV}$	EV battery minimum state of charge, dimensionless
$\eta_{EVc}$	EV battery charging efficiency, dimensionless
$\eta_{EVdc}$	EV battery discharging efficiency, dimensionless
$\varphi_{EV}$	electricity storage loss factor for the EV battery, dimensionless

d. *Stationary storage parameters*

$\overline{cr}_{ST}$	stationary storage maximum charge rate, dimensionless
$\overline{dr}_{ST}$	stationary storage maximum discharge rate, dimensionless
$\overline{SOC}_{ST}$	stationary storage maximum state of charge, dimensionless
$\underline{SOC}_{ST}$	stationary storage minimum state of charge, dimensionless
$\eta_{STc}$	stationary storage charging efficiency, dimensionless
$\eta_{STdc}$	stationary storage discharging efficiency, dimensionless
$\varphi_{ST}$	electricity storage loss factor for the stationary storage, dimensionless

e. *Customer loads*

$D_{B\ m,h}$	microgrid electricity demand, kWh. DER-CAM considers also heating and natural gas loads, but they are not shown in this formulation since we focus on electric storage
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*Decision Variables*

a. *Costs*

$C_{total}$	total annual energy cost of the commercial microgrid, \$
$C_{elec}$	electricity costs, \$
$C_{DER}$	total distributed energy resources costs (amortized capital costs of investments), \$.
$C_{DER*}$	distributed energy resources costs excluding stationary storage, \$.
$C_{fuel}$	fuel costs for fuel based technologies, \$
$C_{DR}$	demand response costs for other non-storage technologies, \$
$C_{EV\ bat}$	EV battery degradation costs, \$
$C_{var\ m,h}$	variable electricity costs (energy and demand charges), \$

$C_{EV\ m,h}$  EV electricity costs, \$

*b. CO<sub>2</sub> emissions*

$CO_2\ total$  total annual commercial building/microgrid CO<sub>2</sub> emissions, kgCO<sub>2</sub>  
 $CO_2\ elec$  CO<sub>2</sub> emissions from electricity consumption, kgCO<sub>2</sub>  
 $CO_2\ fuel$  CO<sub>2</sub> emissions from DG fuel burning, kgCO<sub>2</sub>  
 $CO_2\ EV$  CO<sub>2</sub> emissions from EV electricity exchange, kgCO<sub>2</sub>

*c. Electricity exchange with the micorgrid*

$S_{U\ m,h}$  electricity supplied by the utility, kWh  
 $S_{DER\ m,h}$  electricity supplied by distributed energy resources, kWh  
 $V_{m,h}$  electricity sales, \$

*d. Electricity exchange with EVs*

$D_{EV\ m,h}$  electricity demand from EVs, kWh  
 $E^{c \rightarrow r}_{m,h}$  electricity flow from car to residential building,  $E^{c \rightarrow r} \leq 0$ , kWh  
 $E^{r \rightarrow c}_{m,h}$  electricity flow from residential building to car, kWh  
 $ES_{EV\ m,h}$  electricity stored in EVs, kWh  
 $i_{EV\ m,h}$  EV storage input, kWh  
 $o_{EV\ m,h}$  EV storage output, kWh  
 $S_{EV\ m,h}$  electricity supplied by EVs, kWh

*e. Stationary storage*

$b_{ST}$  stationary storage purchase decision, dimensionless  
 $c_{ST}$  stationary storage installed capacity, kWh  
 $S_{ST\ m,h}$  electricity supplied by local/stationary storage, kWh  
 $D_{ST\ m,h}$  electricity demand from local/stationary storage, kWh  
 $i_{ST\ m,h}$  stationary storage input, kWh  
 $o_{ST\ m,h}$  stationary storage output, kWh  
 $ES_{ST\ m,h}$  electricity stored in stationary storage, kWh

*Objective Function – cost minimization*

The most commonly used objective function in DER-CAM is total energy cost minimization for the microgrid. This includes electricity related costs, amortized capital costs of DER equipment, fuel costs, demand response measure costs, EV battery degradation costs, and sales. Please note that only the storage relevant variables of equation 3 are shown in more detail below. For  $C_{EV\ bat}$  please refer to equation 1.

$$\min C_{total} = C_{elec} + C_{DER} + C_{fuel} + C_{DR} + C_{EV\ bat} - \sum_m \sum_h V_{m,h} \quad (3)$$

$$C_{elec} = \sum_m \sum_h (C_{fix\ m} + C_{var\ m,h} + C_{EV\ m,h}) \quad (4)$$

$$C_{EV\ m,h} = p_{EV} * \left( \frac{E^{r \rightarrow c}_{m,h}}{\eta_{EVc}} + E^{c \rightarrow r}_{m,h} * \eta_{EVdc} \right) \quad (5)$$

$$C_{DER} = C_{DER*} + (C_{STfix} * b_{ST} + C_{STvar} * c_{ST}) * \frac{r}{1 - \frac{1}{(1+r)^{l_{ST}}}} \quad (6)$$

*Objective Function – CO<sub>2</sub> minimization*

As mentioned previously, a second objective function is also available to DER-CAM. In this case, the objective becomes minimizing total CO<sub>2</sub> emissions, which includes

emissions linked to utility electricity and fuel usage, but also to the CO<sub>2</sub> emissions associated with the use of electricity from EVs and their charging at different time periods. Please note that a CO<sub>2</sub> minimization without any cost constraint or space constraint for PV and/or solar thermal would not be meaningful since the solution space would not be constrained and this would mean that unrealistic high numbers of renewable technologies would be adopted to achieve zero CO<sub>2</sub>. A possible way around this is to impose a cost constraint as used in section 4.2.2.

Note also that only the EV relevant variables of equation 7 are shown in more detail below since stationary storage electricity and its related CO<sub>2</sub> emissions can come from any source in equation 7 (macrogrid, onsite DER, and EVs).

$$\min \text{CO}_2 \text{ total} = \text{CO}_2 \text{ elec} + \text{CO}_2 \text{ fuel} + \text{CO}_2 \text{ EV} \quad (7)^1$$

$$\text{CO}_2 \text{ EV} = \sum_m \sum_h \left( \left( \frac{E^{r \rightarrow c}_{m,h}}{\eta_{\text{EVc}}} + E^{c \rightarrow r}_{m,h} * \eta_{\text{EVdc}} \right) * \text{CO}_{2\text{EV-home}_{m,h}} \right) \quad (8)$$

### Constraints

#### a. Balance equations

This includes electric, heating and cooling balance equations, but we focus on the electric balance (equation 9), as this relates to the storage interactions. Other relevant examples are the EV battery specific electric balance equation 10 and stationary storage electric balance equation 11.

$$S_{U,m,h} + S_{\text{DER},m,h} + S_{\text{ST},m,h} + S_{\text{EV},m,h} - V_{m,h} = D_{B,m,h} + D_{\text{St},m,h} + D_{\text{EV},m,h} \quad (9)$$

$$ES_{\text{EV},m,h} = ES_{\text{EV},m,h-1} * (1 - \varphi_{\text{EV}}) + i_{\text{EV},m,h} - o_{\text{EV},m,h} \quad (10)$$

$$ES_{\text{ST},m,h} = ES_{\text{ST},m,h-1} * (1 - \varphi_{\text{ST}}) + i_{\text{ST},m,h} - o_{\text{ST},m,h} \quad (11)$$

#### b. Operational constraints

Operational constraints are applied to all technologies involved in DER-CAM, and are used, for instance to model technology behavior. Highlighted here are the net input and output electric flows from EVs and stationary storage (equations 12 & 13 and 17 & 18), as well as capacity related constraints (equations 14, 15 & 16 and 19, 20 & 21).

$$S_{\text{EV},m,h} = o_{\text{EV},m,h} * \eta_{\text{EVdc}} \quad (12)$$

$$D_{\text{EV},m,h} = \frac{i_{\text{EV},m,h}}{\eta_{\text{EVc}}} \quad (13)$$

$$c_{\text{EV}} * \underline{\text{SOC}_{\text{EV}}} \leq ES_{\text{EV},m,h} \leq c_{\text{EV}} * \overline{\text{SOC}_{\text{EV}}} \quad (14)$$

$$i_{\text{EV},m,h} \leq c_{\text{EV}} * \overline{\text{CF}_{\text{EV}}} \quad (15)$$

$$o_{\text{EV},m,h} \leq c_{\text{EV}} * \overline{\text{dr}_{\text{EV}}} \quad (16)$$

$$S_{\text{ST},m,h} = o_{\text{ST},m,h} * \eta_{\text{STdc}} \quad (17)$$

<sup>1</sup> Please note that DER-CAM could consider cost and CO<sub>2</sub> minimization at the same time in form of a multi-objective optimization, but within this paper we use either the cost or CO<sub>2</sub> minimization objective function and no multi-criteria optimization is performed.

$$D_{ST\ m,h} = \frac{i_{ST\ m,h}}{\eta_{STc}} \quad (18)$$

$$c_{ST} * \overline{SOC_{ST}} \leq ES_{ST\ m,h} \leq c_{ST} * \overline{SOC_{ST}} \quad (19)$$

$$i_{ST\ m,h} \leq c_{ST} * \overline{cr_{ST}} \quad (20)$$

$$o_{ST\ m,h} \leq c_{ST} * \overline{dr_{ST}} \quad (21)$$

### 3 Assumptions

#### 3.1 Building and tariff data

Although, very common at industrial buildings with electric peak loads greater than 5 MW, DERs are mostly overlooked for commercial buildings with loads less than 5 MW. Thus, the focus in this paper is on midsized buildings, between 100-kW and 5-MW electric peak load, and the assumption is that DERs will not be attractive for commercial buildings and microgrids with less than 100 kW peak load.

The starting point for the hourly load profiles used within DER-CAM is the CEUS database, which contains 2,790 premises in total [16]. As can be seen from Figure 3, not all utilities participated in CEUS, the most notable absence being the Los Angeles Department of Water and Power (LADWP) and forecasting zone (FZ) 14+15. For this study, the small zones FZ2 and 6 were also excluded, and we also eliminated the miscellaneous building types for which there is insufficient information for simulation. The remaining solid black slices of the pie represent 68% of the total commercial electric demand. Because the focus here is on mid-sized buildings almost half of the black slices were also eliminated, leaving 35% of the total commercial electric demand in the service territories of Pacific Gas and Electric (PG&E), Southern California Edison (SCE), and San Diego and Gas Electric (SDG&E). These assumptions result in the consideration of 139 representative buildings and they are made up of the following building types in different sizes: hospitals, colleges, schools, restaurants, warehouses, retail stores, groceries, offices, and hotels/motels. Because CEUS buildings each represent a certain segment of the commercial building sector, results from typical buildings can readily be scaled up to the state level by multiplying the building type results with the number of buildings for a certain type [4].

As is typical for Californian utilities, the electricity tariff has a fixed charge plus TOU pricing for both energy and power (demand) charges. The latter are proportional to the maximum rate of consumption (kW), regardless of the duration or frequency of such consumption over the billing period. Demand charges are assessed monthly and may be assessed for all hours of the month, only during certain periods (e.g., on-, mid-, or off-peak) or at the highest monthly hour of peak system wide consumption. For example, for buildings with electric peak loads greater than 500 kW in PG&E's service territory, the E-19 TOU tariff is used. The E-19 consists of a seasonal demand charge between US\$13.51/kW (summer) and US\$1.04/kW (winter), and the TOU tariff varies between US\$0.16/kWh (on-peak) and \$0.09/kWh (off-peak) in the summer months (May to October). Winter months are assumed to have only a US\$0.01/kWh difference between mid-peak and off-peak hours. Summer on-peak is defined from 12:00–18:00 on weekdays. Details of the current 2012 E-19 can be found at [20].

It is assumed that in PG&E and SCE service territories, the EVs can be charged at home at night for US\$0.06/kWh, and in the SDG&E service territory, for US\$0.14/kWh [21].

It is assumed that the electric tariffs stay constant in real terms as nominally observed in 2009. This assumption is justified due to the recently falling natural gas prices and this will limit the cost

increases at the natural gas fired marginal power plants. The natural gas prices are calculated as an average of the observed prices between 2006 and 2009 and are also held constant in real terms. Please note that different buildings, depending on the size and climate zones within CEUS will have different tariffs, and therefore, all commercial utility tariffs and natural gas forecasts used for this paper can be found in [4].

### 3.2 Electric storage technology assumptions

As described in section 2, DER-CAM defines the optimal electric storage capacity the microgrid should consider for adoption in order to achieve the defined objectives. To analyze the effect of future technological improvement in both stationary and mobile electric storage systems, different settings for the storage parameters are assumed. The *base-case* is representing the state of the art of both technologies whereas the *realistic* and *optimistic* cases assume technological improvements leading to better performance. The corresponding parameters settings are given in Table 1 and Table 2.

Table 1: Assumed energy storage parameters for different performance scenarios in 2020

battery performance scenario	stationary electric storage			EV batteries			thermal storage
	base-case	realistic	optimistic	base-case	realistic	optimistic	
charging efficiency	0.85	0.90	0.95	0.85	0.90	0.95	0.90
discharging efficiency	0.85	0.90	0.95	0.85	0.90	0.95	0.90
decay per hour	0.001			0.001			0.01
maximum charge rate	0.10	0.30	0.30	0.45			0.25
maximum discharge rate	0.25	0.30	0.30	0.45			0.25
minimum state of charge	0.30			0.20			0.00

Note: all parameters are dimensionless, except the decay

#### 3.2.1 Charging & discharging efficiency

As indicated by equations 5, 8, 13, and 18 in section 2, charging and discharging efficiency directly affects the total cost and CO<sub>2</sub> emissions of buildings that use electric storages as part of their energy management. Efficiency of charging and discharging strongly depends on the technology used for the involved components. These components are mainly batteries, inverters and, in case of mobile storages, the charging equipment. For stationary batteries the standard technology today are lead acid batteries, which usually have efficiencies between 70% and 85% [22], [23]. For mobile electric storage system in EVs and PHEVs, Li-Ion technology is used today. Current Li-Ion cells have an efficiency around 90% [24], [25]. In the future, further improvements are expected to push this value close to 100% [22]. With the expected future cost reduction Li-Ion cells could also find their way into stationary storage applications leading to a leap in efficiency in this field. These potential improvements are reflected in the assumptions made for the storage parameters. In the base-case an efficiency of 85% is assumed for both stationary and mobile electric storage. For stationary cells this implies latest lead acid technology with highly efficient inverters. For mobile application this would be Li-Ion with an efficiency of 90% and losses in the charging equipment. With the use of Li-Ion cells in stationary storage, further improvement in Li-Ion cell efficiency and reduction of losses in charger efficiency in both applications could improve to 90% or even 95% in an optimistic case.

#### 3.2.2 Charging & discharging rates

The charging and discharging rate (c-rate) defines the ration of charging power to energy capacity of the electric storage. This is a relevant parameter for the building management system since it defines the maximum power the battery can absorb or provide during an hour. Charging and discharging with high power to energy ratio means more stress to the batteries and reduces their lifetime [26]. In order to minimize this stress the energy management system defines the maximum discharge rates for stationary electric storage (see Table 1). Using more advanced Li-Ion batteries, mobile storage is more resistant to higher charging and discharging rates. During driving, PHEV batteries are bearing much

higher c-rates without showing significant effect on their lifetime [27]. In this paper, when plugged to the building their c-rate is limited to 0.45 due to technical constraints of the charging equipment.

### **3.2.3 Battery Decay**

The cell decay defines the electricity losses of the cell due to self-discharge, which also has an effect on the way electric storage are used by the building energy management system. For both stationary and mobile storages a self-discharge rate of 0.1% per hour is assumed. A decay of 0.1% means that after roughly 40 days 40% of a full charged battery is available for driving or building usage.

### **3.2.4 Minimum state of charge**

Electric storage operation is affected by constraints in the state of charge (SOC) of the batteries. Both deep discharging and high charging lead to reduced lifetime of batteries. Therefore, the energy management system has to keep the battery's SOC within a defined range to minimize storage degradation. For stationary batteries a minimum SOC of 30% is assumed, which is the minimal SOC for lead acid batteries that should be observed to reach high cycle life [22]. For mobile storage with Li-Ion batteries a minimum SOC of 20% is feasible without considerably affecting cycle life.

### **3.2.5 Storage capital cost**

Capital costs for storage is another important parameter for the adoption and use of electric storage in microgrids. Capital costs are defined by the initial investment costs and the life time of the cells. For stationary storage investment costs are split up into a fixed part and a variable part. The fixed part captures the costs for integration of the storage into the microgrid or building as well as costs for permits, whereas the variable part includes the capacity-dependent investment cost of the batteries (see Table 3). Due to their relatively low specific costs lead acid batteries are the first choice for local stationary electric storage today. With costs ranging from \$100/kWh to \$400/kWh they are setting the economic benchmark in this field [22], [23].

Lifetime of batteries is usually defined by their cycle-life, which indicates the maximum number of cycles within a defined range (maximum charge & discharge) the battery should withstand. Cycle-life of lead acid batteries typically ranges from 500 to 2000 cycles [22], [23]. In this analysis, a stationary battery-lifetime of 5 years is assumed, which is equivalent to 1000-1500 cycles with roughly one cycle a day at a standard usage pattern.

As described in section 2 costs of mobile storage in DER-CAM are calculated as equivalent compensation for battery degradation caused by the use of the microgrid EMS. Hence, cost of mobile storage use depends on degradation and replacement cost of the batteries. Battery degradation is estimated according to the model formulated by [27] & [28]. According to the experimental results for lithium-iron-phosphate batteries, degradation can be defined as a function of the energy processed. Therefore, the derived degradation provides a convenient basis to quantify the exact compensation the microgrid has to pay for energy processed through the mobile storage for EMS usage. For EV batteries replacement costs of \$200/kWh are assumed, which is in the range of estimations for 2020 costs of EV batteries [29].

## **3.3 Distributed Energy Resources (DER) Technologies**

Since DER-CAM does not consider storage technologies in isolation, other possible DER technologies for the commercial buildings need to be defined. Please note that DER-CAM distinguishes between discrete technologies, which can be picked only in discrete sizes. On the other hand, continuous technologies are available in almost all sizes. The advantage of having discrete technologies is to be able to model economies of scale by specifying multiple units with different sizes and costs in an accurate way. However, the disadvantage of having discrete technologies is that the optimization turns into a mixed integer problem and this increases the run-time. Thus, from an optimization stand point it is preferable to define technologies as continuous ones to reduce the optimization runtime.

Table 2: Available discrete technologies in 2020 [30], [31], [32]<sup>2</sup>

		ICE		GT	MT		FC	
		S	M		S	M	S	M
capacity (kW)		60	250	1000	50	150	100	250
installation cost (\$/kW)		2721	1482	1883	2116	1723	2382	1909
		w/HX	3580	2180	2580	2377	1936	2770
maintenance cost (\$/kWh)		0.02	0.01	0.01	0.02	0.02	0.03	0.03
electrical efficiency <sup>3</sup> (%)		29	30	22	25	26	36	36
HPR (if w/HX)		1.73	1.48	1.96	1.80	1.30	1.00	1.00
lifetime (years)		20	20	20	10	10	10	10

Notes: All technologies running on natural gas. *S* – small-sized model, *M* – medium-sized model, *w/HX* – with heat exchanger (using combined heat and power capabilities), *HPR* – heat-power ratio, *ICE* – internal combustion engine, *GT* – gas Turbine, *MT* – microturbine, *FC* – fuel cell.

Table 3: Available continuous DER technologies in 2020 [31], [32], [33], [34], [35], [36], [37]

	ES	TS	FB	AC	ST	PV
fixed costs <sup>4</sup> (\$)	295	10000	0	93911	0	3851
variable cost (\$/kW, or \$/kWh when referring to storage)	200/150 <sup>5</sup>	100	220	685 <sup>6</sup>	500	3237
maintenance cost (\$/kWh)	0	0	0	1.88	0.5	0.25
lifetime (years)	5	17	10	20	15	20

Notes: *ES* – stationary energy storage, *TS* – thermal storage, *FB* – Flow Battery, *AC* – Absorption Chiller, *ST* – solar thermal system, *PV* – photovoltaic.

## 4 Results

### 4.1 Performed runs

As shown in Table 1 three performance scenarios (*base-case*, *realistic*, and *optimistic*) for storage technologies are researched in this paper for the year 2020. However, the considered 139 different commercial buildings that could utilize electric vehicles or stationary storage can have different optimization strategies: a) building energy cost<sup>7</sup> minimization and b) CO<sub>2</sub> emission reduction<sup>8</sup>. Thus, the three performance scenarios are subject to these two basic optimization strategies. In the CO<sub>2</sub> minimization case a 30% cost increase cap is applied to limit the economic impact to the microgrids. All these runs are considered as run set A.

A second run set B is performed, with only changed variable costs for stationary storage to look into the impact of lower costs on other DER at the building. The variable costs for stationary storage are reduced to \$150/kWh in run set B.

For each performance scenario (*base-case*, *realistic*, and *optimistic*) 139 optimization runs were performed, reflecting the selected commercial buildings and the results were aggregated to the state level. In this way, almost 1700 optimization runs were performed in total, resulting in almost 100

<sup>2</sup> Please note that we report turn-key costs.

<sup>3</sup> Higher heating value

<sup>4</sup> Fixed costs do not depend on the size of the adopted technology and reflect permitting costs or fixed engineering costs.

<sup>5</sup> \$150/kWh is used in run set B. Please refer to section. 4.3.

<sup>6</sup> Absorption chiller costs are expressed in \$/kW electric equivalent of an electric chiller.

<sup>7</sup> Includes amortized capital costs.

<sup>8</sup> To be able to access the CO<sub>2</sub> reduction due to DER adoption hourly marginal grid CO<sub>2</sub> emission rates were estimated based on [38].



hours of optimization time. Cost and CO<sub>2</sub> savings are compared to a so called do-nothing case in which all the building energy needs are purchased from the local utility and no DER adoption is allowed.

## 4.2 Aggregated results for California, run set A

Table 4 shows the aggregated results for each battery performance scenario and the two major optimization strategies for run set A with the assumptions described in section 3.

Table 4: Aggregated results for run set A<sup>9</sup>

		do- nothing *	minimize costs			minimize CO <sub>2</sub> **		
			base- case	realistic	optimistic	base- case	realistic	optimistic
aggregate energy costs	(billion \$)	5.22	4.85	4.82	4.79	6.78	6.78	6.78
CO <sub>2</sub> emissions at microgrids	(million t)	20.50	19.69	19.63	19.53	12.58	12.27	12.16
number of EVs EMS would like to utilize	(million cars)	-	1.71	1.85	2.19	0.25	0.26	0.35
connected electric mobile storage	(GWh)	-	41.03	44.50	52.52	5.90	6.24	8.43
adopted electric stationary storage	(GWh)	-	0.03	0.01	0.25	13.93	12.94	13.66
adopted PV at microgrids	(GW)	-	0.23	0.23	0.21	4.56	4.83	4.82
adopted CHP and DG at microgrids	(GW)	-	1.42	1.50	1.46	3.73	3.83	3.73
natural gas fired CHP & DG generation	(TWh)	-	7.43	7.30	7.11	16.67	16.87	16.92
average CHP & DG capacity factor	(%)	-	59.61	55.63	55.67	50.95	50.22	51.78

EMS - energy management system ; DG – distributed generation; CHP – combined heat and power;

\*do-nothing: all energy is purchased from the utility

\*\*the average max. cost increase due to CO<sub>2</sub> minimization was set to 30% and is constrained within DER-CAM

### 4.2.1 Discussion of the microgrid cost minimization strategy for run set A

The minimize cost strategy shows cost savings for the considered commercial buildings between 7% and roughly 8%, with the higher savings for the optimistic battery performance assumptions. The CO<sub>2</sub> emissions are reduced by roughly 4% to 4.7%, again showing the higher savings for the optimistic battery performance assumptions (see Table 4).

Electric mobile storage plays a dominant role in the cost minimization cases and between 1.7 and 2.2 EVs will be connected to the commercial buildings/microgrids throughout the year and used by the EMS to achieve the cost minimization objective. PV and stationary storage are insignificant, although optimistic stationary storage performance parameters for 2020 help stationary storage adoption. Natural gas fired DER, mostly in form of internal combustion engines, play a role in these cases and between 1.4 and 1.5 GW will be adopted at the microgrids.

Increased charging and discharging efficiencies mostly help the EV adoption since with a cost minimization objective the major strategy will be to transfer cheap electricity from the residential building to the commercial microgrid. Please note that commercial buildings observe higher electric rates as well as demand charges during the day, compared to the EV home charging rates (see also section 3.1 for tariff information). Also, note that the charging and discharging efficiency are set equal

<sup>9</sup> Please note that Life-Cycle-Assessments are not part of this work.

for stationary and mobile storage in the different performance scenarios, and therefore, the changes in EV batteries and stationary storage can be compared directly (see also section 3.2).

#### 4.2.2 Discussion of the microgrid CO<sub>2</sub> minimization strategy for run set A

As already mentioned, the CO<sub>2</sub> minimization runs use a cost cap of 30% to constrain the economic impact on the commercial building owners. A 30% increase is roughly equal to a 3% annual increase over ten years and seems to be justifiable. This cap manifests in \$6.78 billion energy costs as shown in Table 4.

Most importantly, the CO<sub>2</sub> minimization runs show impressive CO<sub>2</sub> reductions around 40%. In contrast to the cost minimization runs, the CO<sub>2</sub> minimization runs show that stationary storage plays a prominent role and between 13 GWh and 14 GWh will be adopted (see also Table 4). EV batteries are reduced and only between 0.3 and 0.4 million EVs will be connected to the commercial buildings. The elevated PV capacity hints to the reason for the dramatically increased stationary storage capacities: stationary storage in combination with PV is a CO<sub>2</sub> emission reduction measure for the microgrid, but not EV batteries, which depart in the afternoon or evening. Renewable energy stored in the EV batteries would be used somewhere else in the evening or night, and therefore, do not support the CO<sub>2</sub> reduction strategy of the commercial buildings in the microgrid.

Finally, a CO<sub>2</sub> minimization strategy also results in elevated natural gas fired engines, mostly efficient combined heat and power (CHP) fuel cell technologies. However, as shown in Table 4 the run time of CHP is reduced as indicated by the average capacity factors.

#### 4.3 Aggregated results for California, lower stationary storage costs, run set B

Results for a stationary storage investment cost sensitivity are shown in this section. Run set B assumes stationary storage costs of \$150/kWh and all other technology assumptions are unchanged compared to run set A.

Table 5: Aggregated results for run set B with lower stationary storage costs

		do-nothing *	minimize costs			minimize CO <sub>2</sub> **		
			base-case	realistic	optimistic	base-case	realistic	optimistic
aggregate energy costs	(billion \$)	5.22	4.85	4.81	4.76	6.78	6.78	6.76
CO <sub>2</sub> emissions at microgrids	(million t)	20.50	19.69	19.66	19.53	12.27	11.93	11.89
number of EVs EMS would like to utilize	(million cars)	-	1.67	1.96	2.24	0.26	0.26	0.33
connected electric mobile storage	(GWh)	-	40.13	47.06	53.68	6.13	6.33	8.02
adopted electric stationary storage	(GWh)	-	0.03	0.37	1.51	18.94	17.60	17.79
adopted PV at microgrids	(GW)	-	0.23	0.24	0.23	5.21	5.44	5.32
adopted CHP and DG at microgrids	(GW)	-	1.42	1.39	1.22	3.74	3.72	3.68
natural gas fired CHP & DG generation	(TWh)	-	7.42	7.04	6.89	15.67	15.67	15.77
average CHP & DG capacity factor	(%)	-	59.56	57.67	64.59	47.77	48.05	48.97

EMS - energy management system ; DG – distributed generation; CHP – combined heat and power;

\*do-nothing: all energy is purchased from the utility

\*\*the average max cost increase due to CO<sub>2</sub> minimization was set to 30% and is constrained within DER-CAM

#### 4.3.1 Discussion of results for run set B

The major observations from run set A are still valid:

- EV batteries are used especially in the cost minimization cases
- stationary storage and PV are insignificant in the cost minimization cases, and
- stationary storage, PV, and fossil based CHP play a dominate role in CO<sub>2</sub> minimization cases.

Table 6: Comparison between run set B and A with run set A as basis

		minimize costs			minimize CO <sub>2</sub>		
		base-case	realistic	optimistic	base-case	realistic	optimistic
aggregate energy costs	%	0	0	-1	0	0	0
CO <sub>2</sub> emissions at microgrids	%	0	0	0	-2	-3	-2
number of EVs EMS would like to utilize	%	- 2	6	2	4	1	- 5
connected electric mobile storage	%	- 2	6	2	4	1	- 5
adopted electric stationary storage	%	- 19	2,422	500	36	36	30
adopted PV at microgrids	%	- 2	1	10	14	13	10
adopted CHP and DG at microgrids	%	0	- 7	- 16	0	- 3	- 1
natural gas fired CHP & DG generation	%	0	- 4	- 3	- 6	- 7	- 7
average CHP & DG capacity factor	%	0	4	16	- 6	- 4	- 5

The 25% reduction in stationary costs helps the stationary storage adoption significantly in all cases, except the minimization cost base-case. In this case however, due to the small stationary numbers the change is not significant. Please note that the highest increases in stationary storage adoption are shown in the cost minimization cases, but the absolute numbers are significantly below the CO<sub>2</sub> minimization cases. In general, it can be said that the reduced stationary storage costs increase the stationary storage capacity by more than 25%, increase the PV adoption by up to 14%, and reduce the adopted CHP capacity by up to 16%. These results demonstrate how complex the interactions between DER technologies can be, justifying a complex optimization algorithm as used in DER-CAM.

## 5 Conclusions

The complex interactions of buildings and electric vehicles require a building centric optimization approach that captures the benefits of building linked distributed energy resources (DERs) and electric vehicles in a holistic way. Only such an integrated approach will enable unused efficiency potentials and show possible problematic interactions between DER technologies. In this context, EVs are seen as an additional resource for microgrids or commercial buildings. Other resources at the microgrid can be fuel cells, PV, solar thermal, stationary storage, absorption cooling, combined heat and power, etc. All these technologies are considered as equal options and can help building energy management systems or microgrid controllers to achieve cost or CO<sub>2</sub> reduction goals by managing them. The deployment of these resources by commercial microgrids requires decision support that simultaneously treats investment and operations. In order to illustrate the benefits and challenges of the incorporation of EVs into a microgrid, we model the decisions of various types of California users in different geographical regions. To test the robustness of the results different stationary storage and mobile storage parameter scenarios have been analyzed and reported in this paper. Via DER-CAM, a

mixed integer linear problem, we find that the use of mobile energy storage provided by EVs in commercial buildings is driven more by cost reduction objectives than by CO<sub>2</sub>-reduction/efficiency improvement objectives. Under pure cost minimization, EVs are mainly used to transfer low-cost electricity from the residential building to the commercial microgrid to avoid high demand and energy charges during expensive day hours. By contrast, with CO<sub>2</sub> minimization strategies, the use of stationary storage is more attractive compared to EV storage, because stationary storage is available at the commercial buildings in a microgrid for 24 hours a day and readily accessible for energy management. Also cost reductions in stationary storage demonstrate the complex interactions between the available DER technologies at the microgrids. Lower stationary storage costs increase not only the stationary storage adoption, but also the PV adoption, decrease the CHP adoption, but can also increase the run-time of the CHP units depending on the objective of the microgrid. This demonstrates the necessity for a building integrated optimization approach, as exercised with DER-CAM. However, some limitations apply to the shown approach. Most notably, the uncertainty based nature of some DERs (e.g. PV) and EV driving patterns. Although sensitivities on different EV connection periods have been performed within this work a stochastic programming approach is under way and will be demonstrated in a next step.

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## Appendix

Please note 1700 optimization runs were performed within this work and it is not possible to show all detailed results and technology combinations for them. However, for illustrative purposes we show two diurnal electricity patterns for a medium sized school in the forecasting zone (FZ) 5 (PG&E in the San Francisco Bay Area) for run set A, with the realistic battery performance assumptions scenario considering a cost and CO<sub>2</sub> minimization objective.

Please note that in Figure 4 and 5 the mobile storage is related to the second y-axis on the right hand-side. Both pictures show that with CO<sub>2</sub> minimization strategy less mobile storage is adopted and that PV generates electricity at the same time when mobile storage delivers energy. Furthermore, when mobile storage disconnects from the building at 18:00 the natural gas fired engines and stationary storage deliver parts of the energy in the CO<sub>2</sub> minimization case.

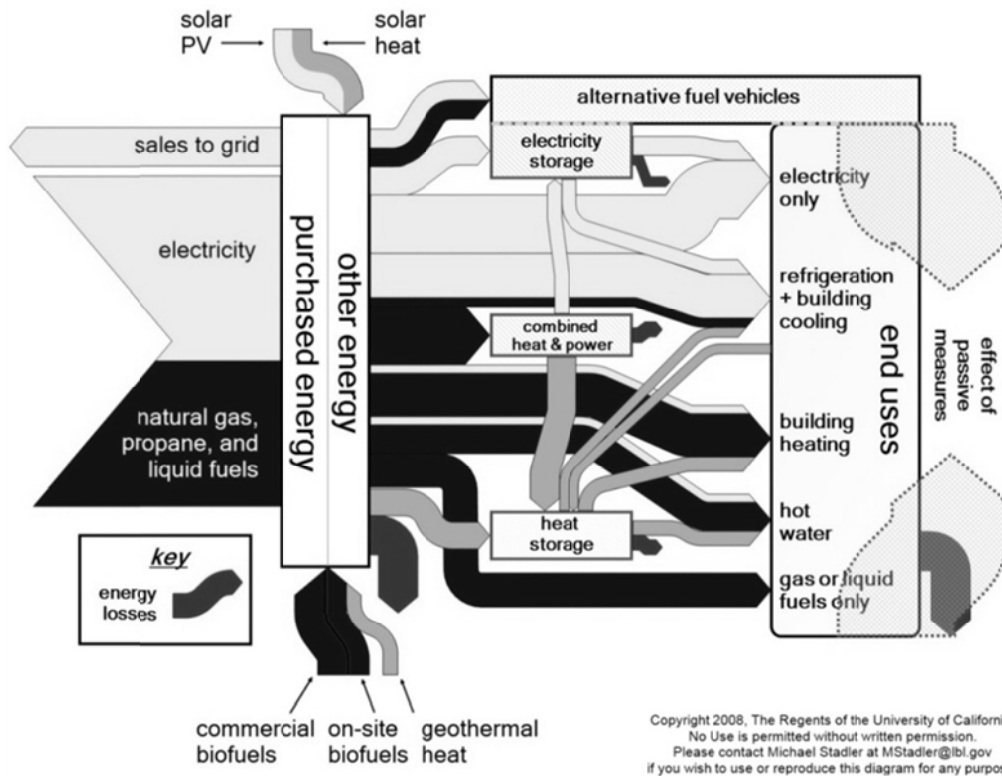


Figure 1: High level schematic of DER-CAM, including alternative fuel vehicles, e.g. electric cars

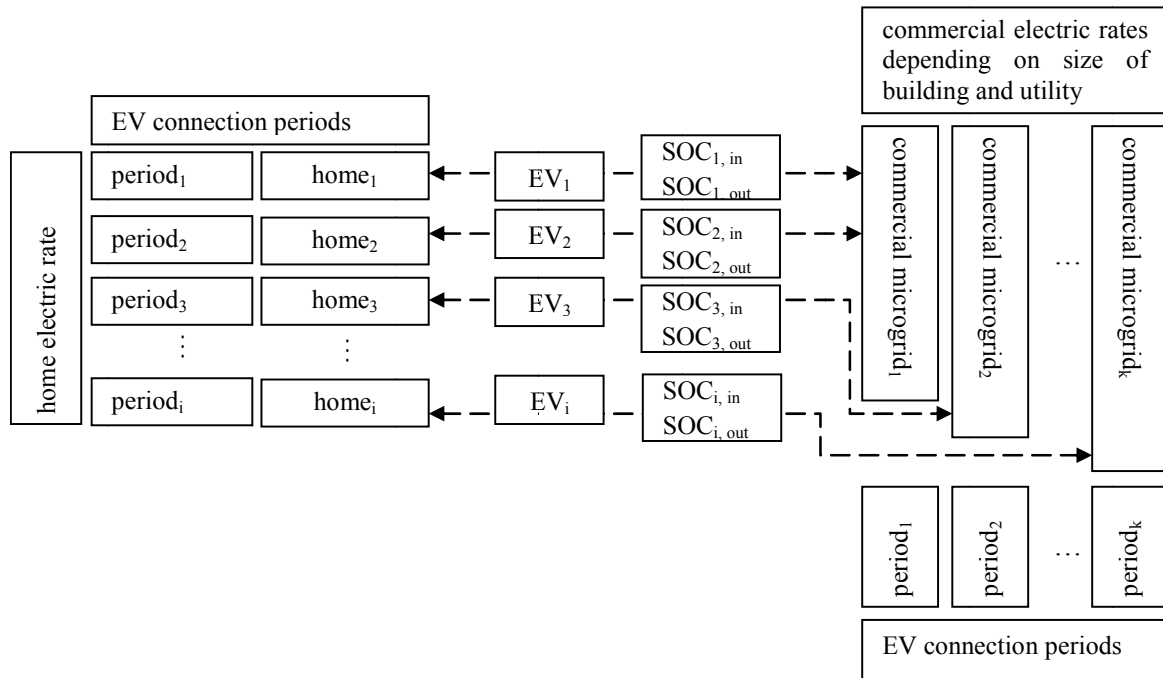


Figure 2: EV modeling in DER-CAM

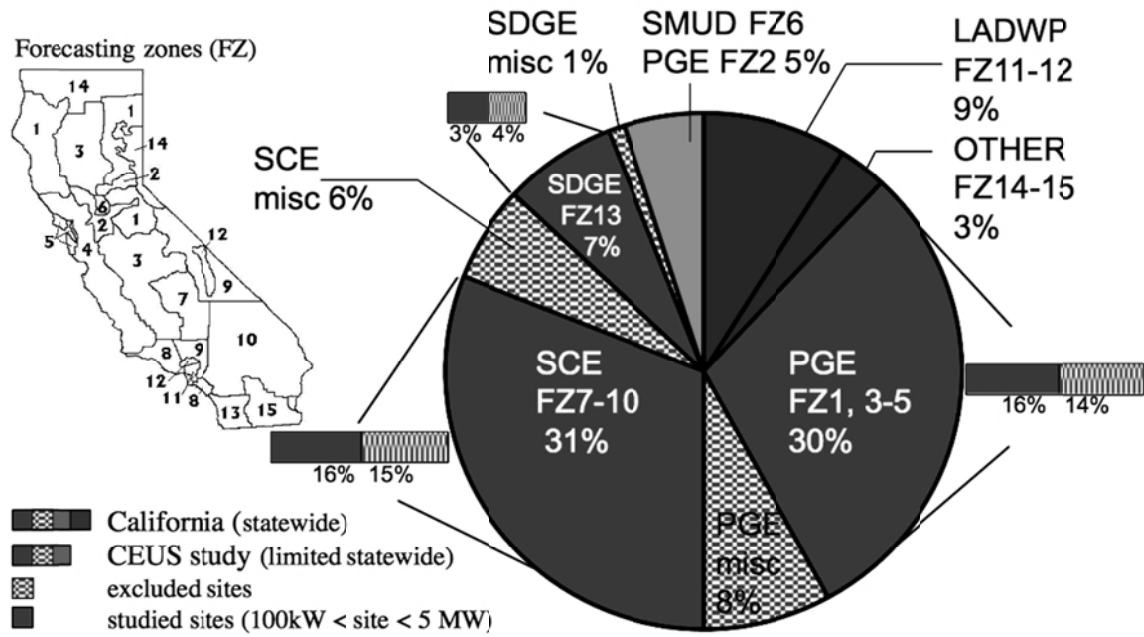


Figure 3: Commercial Electric Demand Fractions

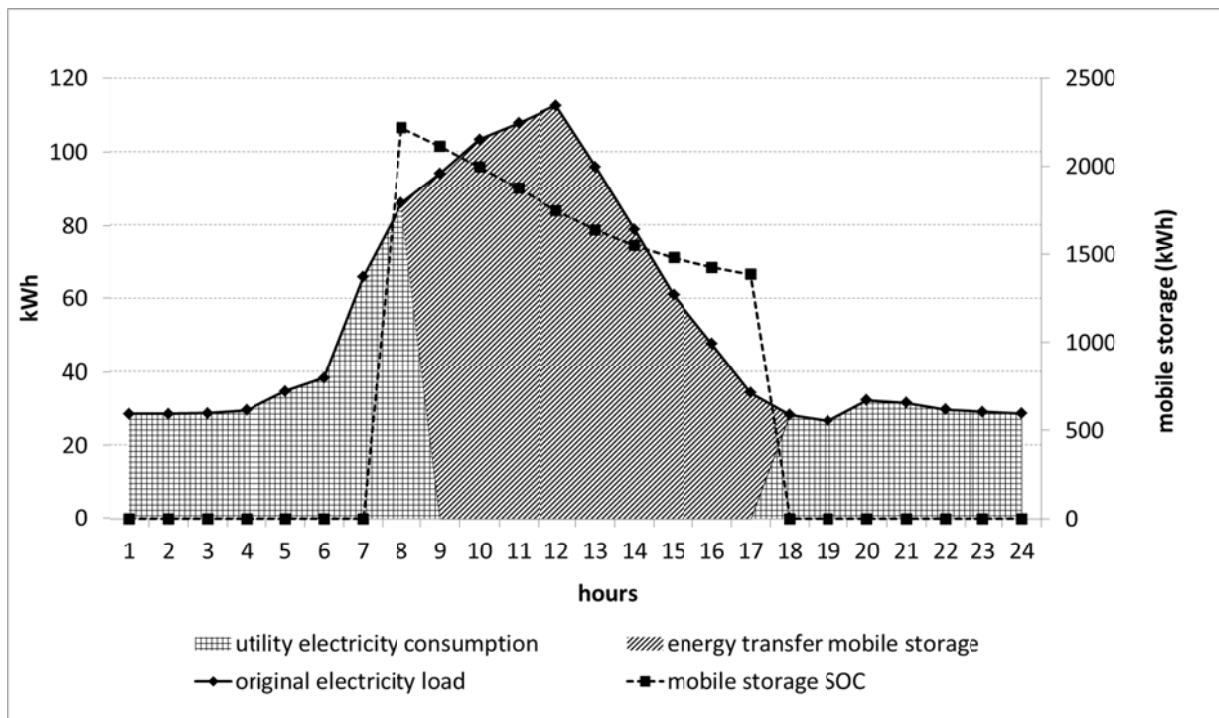


Figure 4: Diurnal electricity pattern for a medium sized school in FZ5 in July, realistic battery performance assumptions and cost minimization

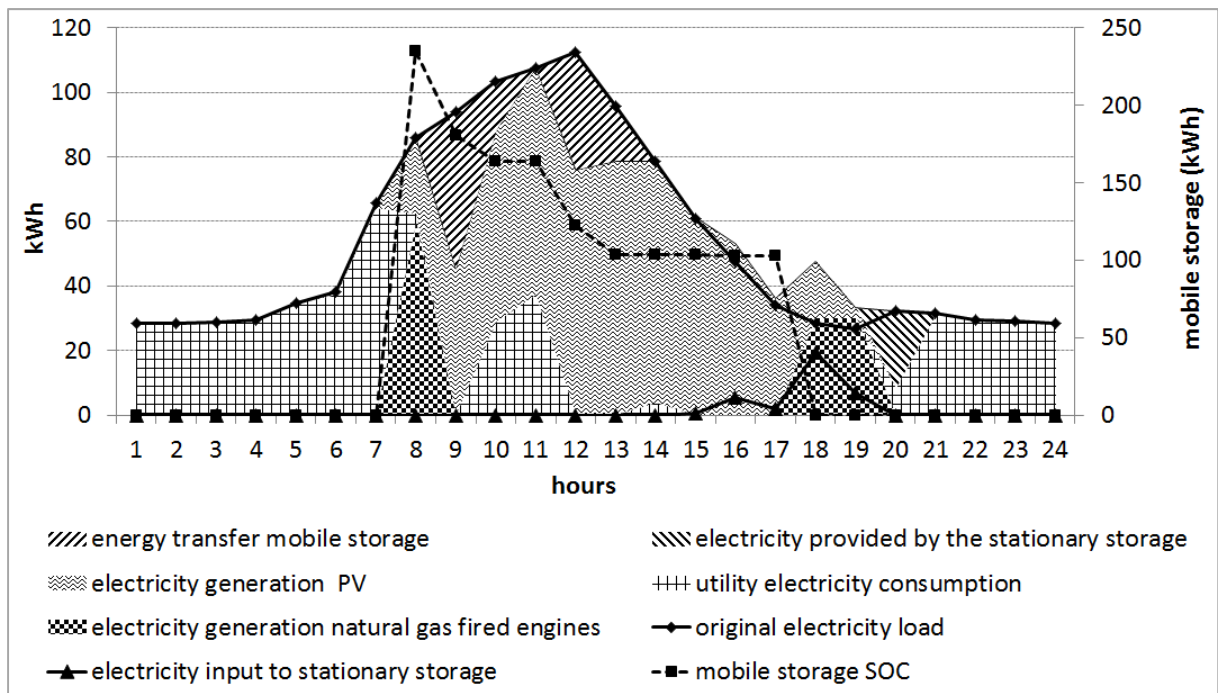


Figure 5: Diurnal electricity pattern for a medium sized school in FZ5 in July, realistic battery performance assumptions and CO<sub>2</sub> minimization